From Habitat to Retina: Neural Population Coding using Natural Movies

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Background

Population retinal responses to natural stimuli is still an open research field, nevertheless retinal ganglion cells (RGC) spatio-temporal correlations may be related to population coding (1). Here, we use a diurnal rodent retina (*O. degus*), which has the advantage of present a 3:1 proportion of rods and cones (2), respectively, to study the RGC population responses to *habitat-based natural stimuli*. In order to do this, we have developed a mobile robot that is capable to record movies in the natural habitat of this rodent, simulating both his movements and the eye-ground distance, which allows us to stimulate and record an in vitro retina patch using MEA (multi electrode array) with a sequence of images taken from the animal natural habitat. The analysis of spike statistics has been done using the Enas software (http://enas.gforge.inria.fr/v3/) allowing to characterize spatio-temporal pairwise correlations, in contrast to e.g. Ising models, that analyze only instantaneous spatial correlations.

Using our robot we obtained a movie of the natural habitat composed of trees, grass, mountains, blue sky, optic flow in several directions and different simulations of the head movement. Natural movies **(NI)** presents high spatial and temporal correlation (Figure 1c, 1d)(3) whereas white noise **(WN)** presents no spatial or temporal correlation (by construction).

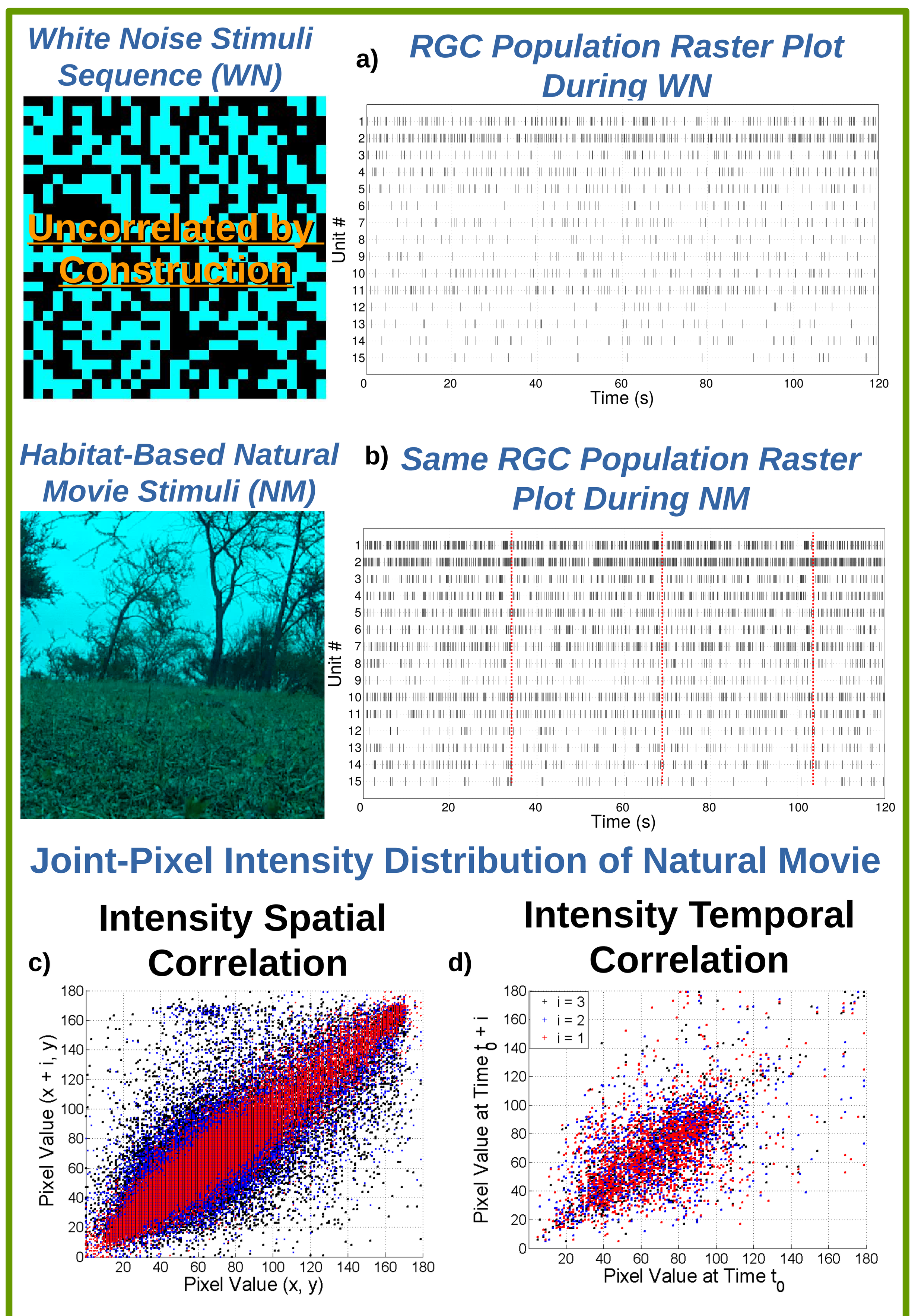


Figure 1. a) White noise stimuli sequence and the response of a RGC population to 120s of the ~1800s complete sequence. **b)** One frame of the ~1900 frames of the natural movie and the responses of the same RGC population during 120s, when the movie was repeated 4 times. Spatio-temporal correlated firing patterns are visible. **c)** Joint-pixel intensity distribution of all pixels and the neighbor ones in one frame of the **NM**. **d)** Joint-pixel intensity distribution of one pixel and the same one along successive frames of the **NM**.

Goals

> ***Classify and select a RGC population according to their temporal filter profile.***

> ***Study the spatio-temporal pairwise correlations of the selected RGC population modeling their activity during WN and NM using Gibbs potential.***

> ***Look for statistical differences/equivalences between the model for NI and WN.***

Methods

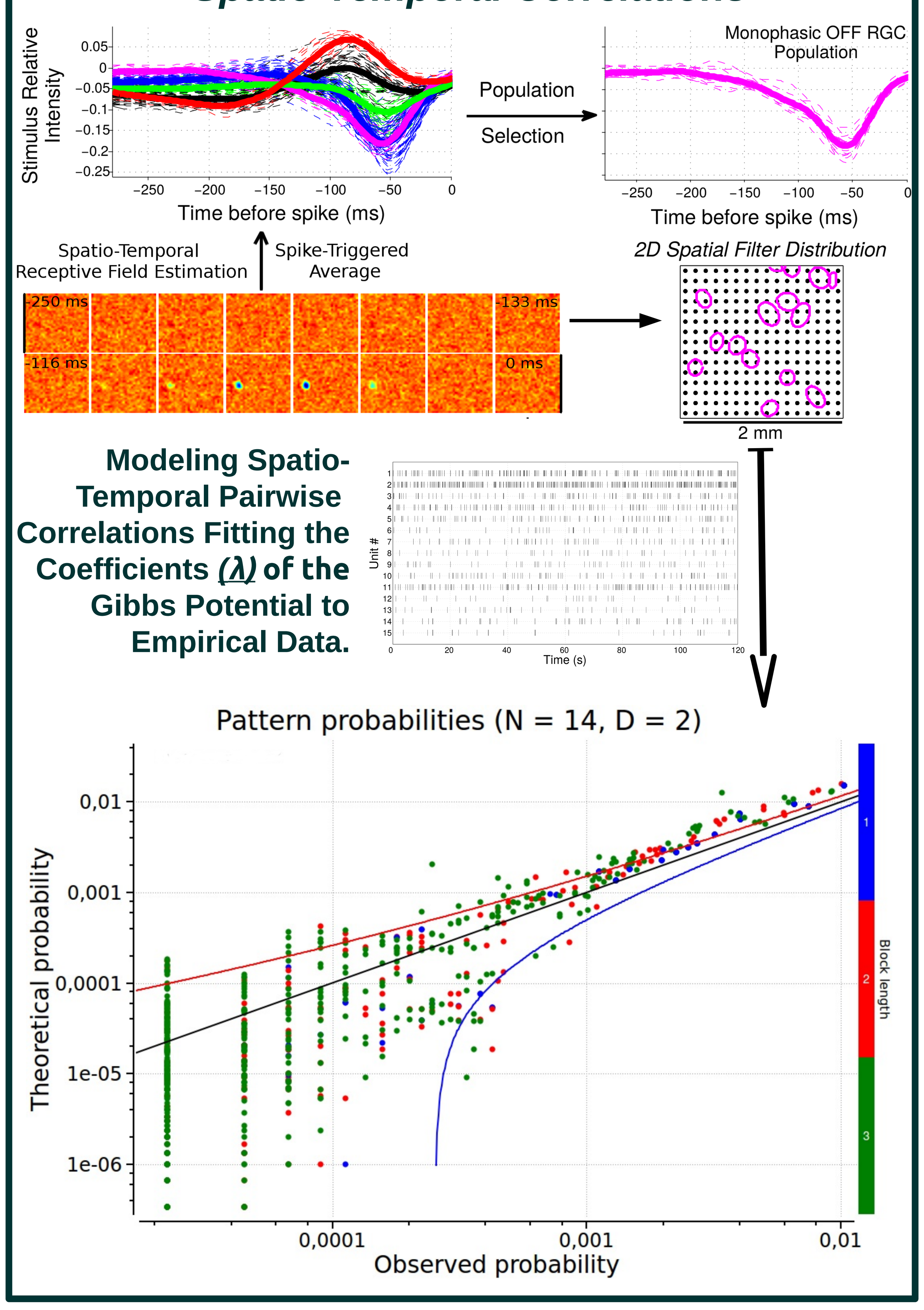
Three retina patch were extracted from 2 different *O.degus* eyes and then recorded using MEA-256 (MultiChannel Systems) during i) spontaneous activity **(SA)** (5-10 min), ii) **WN** (30 min, 60 fps, 50μm) and iii) **NM** (30 or 60 s sequence, 30 trials, 60 fps). Spike sorting were carried out off line using OfflineSorter (Plexon inc.), detecting spikes on each channel with a threshold of -5 S.D. of the signal mean. Then, semi-automatic sorting were performed using ValleySeek or T-Dist E-M algorithm, fitting each class manually. We detect ~ 200 units per patch, whose STA was calculated, obtaining the temporal and 2D spatial filter. RGC were classified according their temporal filter, choosing a group of 14-16 units sharing the same time-to-peak and a monophasic OFF temporal profile.

The selected populations were then analyzed using ENAS software, which fits a Gibbs distribution with spatio-temporal constraints (4) to the empirical data using the maximum-entropy principle. It uses as constrains the empirical spike rate, the pairwise correlations in a 20ms time window (spatial pairwise correlation) and the pairwise correlations with a delay of one time window (temporal pairwise correlation).The free terms fitted are the Gibbs coefficients, which are multipliers (λ) for every observable event (ω) of the Gibbs potential:

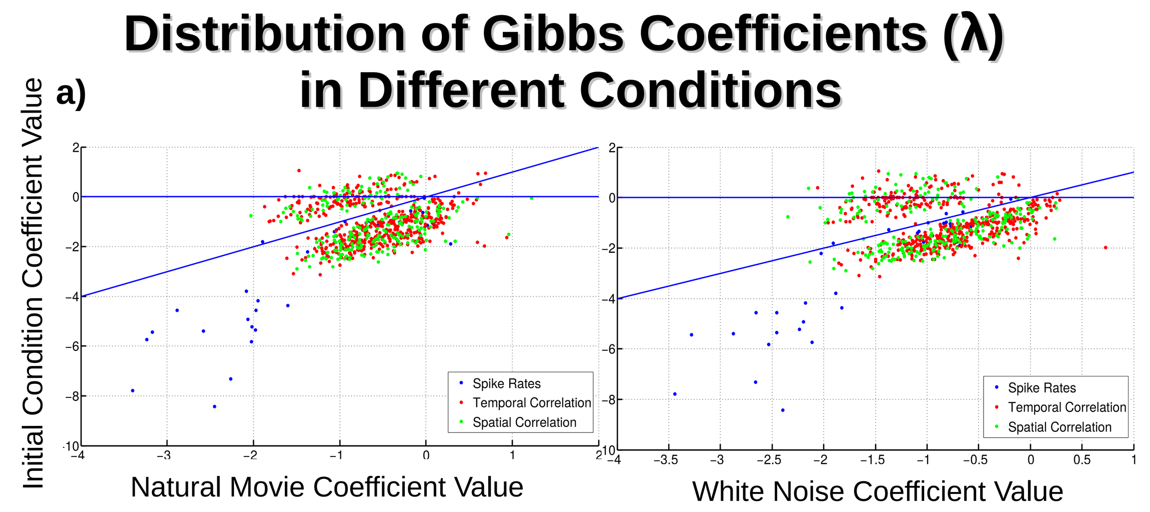
$$\mathcal{H}_{PR}\left(\omega_0^D\right) = \sum_i \lambda_i \omega_i(D) + \sum_{s=0}^{D}\sum_{ij} \lambda_{ij}^s \omega_i(0)\omega_j(s)$$

D is the successive temporal windows in which an observable, *ω*, occurs. In this case, we use *D* = 2. *i* and *j* are the neuron indexes. Then, we computed a symmetric variant of the Kullback-Leibler divergence (5) and took only the real part to make comparisons between conditions and between observables types.

Population Selection and Modeling Pairwise Spatio-Temporal Correlations

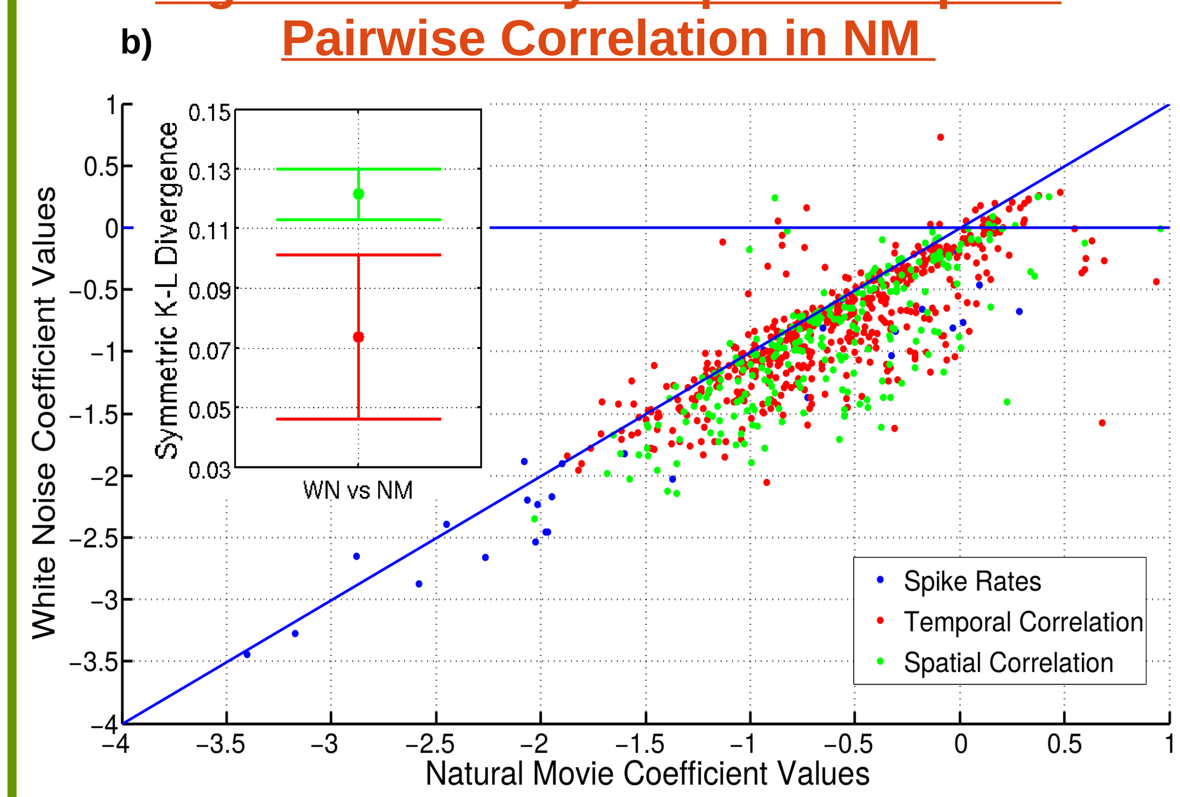


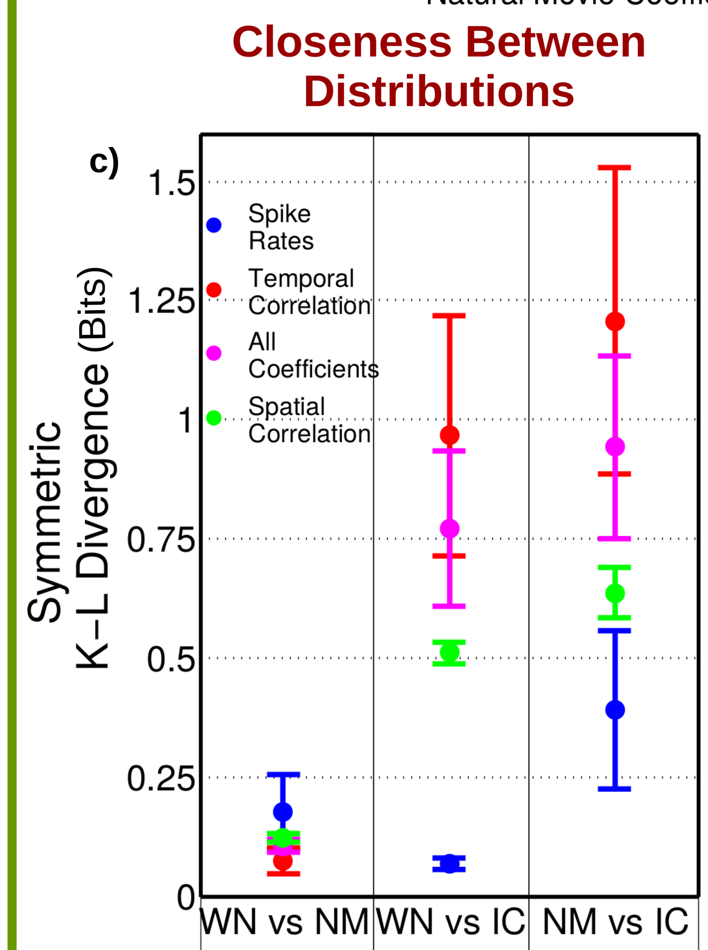
Results



a) Scatter Plots of the Gibbs Coefficients. Blue diagonal line is identity. The two panels show **WN** and **NM** vs **IN**, where we found that the *Spike rates* coefficients are bigger for the two visual stimulation conditions. It also shows clustering above and below the identity Since **IC** is an scotopic/mesopic condition, the inputs for the RGC are different, so it becomes difficult to compare with the photopic conditions. However, those scatter plots are useful to easily detect changes in the probability of the events between 2 conditions.

Higher Probability of Spatio-Temporal Pairwise Correlation in NM





b) Scatter Plot for WN vs NM. We found that *Spike rates* coefficients distributes along the identity, showing that the is no big changes in the firing rate. *Spatial* and *Temporal* correlation coefficients are distributed mostly under the identity, which means that there is higher probability to find spatio-temporal correlated events in NM condition than in WN. So, we suggest that the statistical properties of the natural stimuli are increasing correlated events in the studied population and this is in agreement with K-Pairwise models for both conditions (6).

The inset panel shows the closeness between the distribution of observables types coefficients. We use a symmetric variant of Kullback-Leibler divergence to compute the closeness between two distributions.

c) Closeness Between Gibbs Coefficients Distributions and its Event Types. The two photopic conditions (WN and NM) has closer distributions, in contrast with IC, which is farthest from the other two. Even though *All Coefficients* of IC distribution deviates from the photopic ones, they are closer in *Spike rates* coefficients. In contrary, correlated coefficients are farther. There is big closeness between WN and NM, being the *Spatial correlation* coefficients which are farthest (inset panel in **b**).

Conclusions

> **Gibbs potential constitutes a useful tool for comparing pairwise spatio-temporal correlations between different conditions for the same RGC population. Here, ENAS is a powerful software for modeling the spiking patterns of neuronal populations.**

> **Statistical properties of visual stimuli modulates the pairwise correlations of a population of RGC which shares common characteristics, such as their spatial and temporal receptive field filters.**

> **Spatial correlated spiking patterns represents the mayor deviation between WN and NM conditions. Thus, we purpose that population coding for this monophasic OFF RGC population is mostly (but not only) based on spatial correlation when stimulated with Natural Movies.**

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